Learning with context feedback loop for robust medical image segmentation

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Presentation outline

Medical image segmentation

Clinical applications

- Medical image analysis
- Clinical interventions
- Extrapolate clinical information

Promising approach

- Deep learning methods
- Driving factors
  - Data
  - Processing power
  - Algorithm development

Deep learning methods for medical image segmentation

- FCN [1]
- U-Net [2]
- Embedding shape models [3]

- Transfer learning [4]
- Attention based models [5]
- Post-processing or cascaded models [6, 7]

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[1] Noh, H., *et al.* (2015), CVPR.
[2] Ronneberger O., *et al.* (2015), MICCAI.
[3] Oktay O., *et al.* (2017), IEEE Trans Med Imaging.
[4] Gu Z., *et al.* (2019), IEEE Trans Med Imaging.
[5] Schlemper J., *et al.* (2019), IEEE Trans Med Imaging.
[6] Larrazabal A.J., *et al.* (2020), IEEE Trans Med Imaging.
[7] Painchaud N., *et al.* (2020), IEEE Trans Med Imaging.

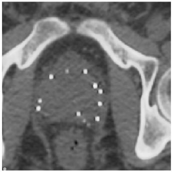
Deep learning methods for medical image segmentation

Success

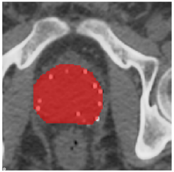
- Automatically extract distinctive image features
- Achieved promising quantitative results

Challenges

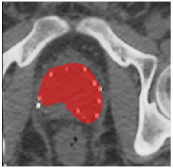
- Strongly biased towards recognizing texture features [1]
- Produce unrealistic and incomplete segmentation



Input image



Reference



Predicted

[1] Geirhos R., *et al.* (2018), ICLR.

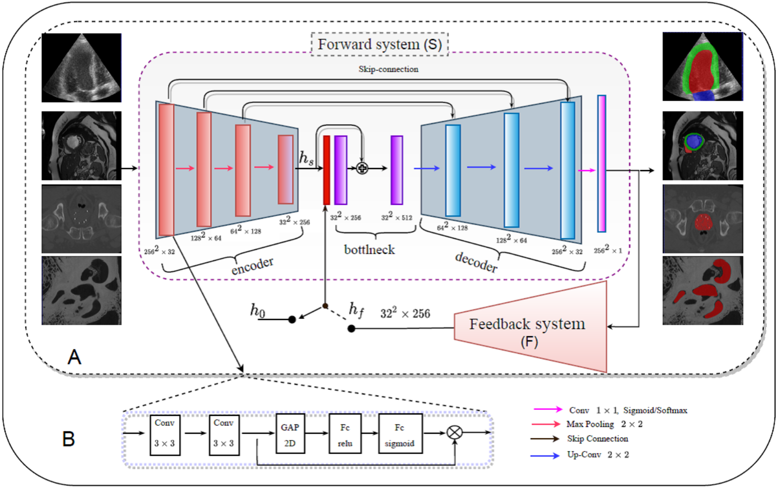
Learning with context feedback loop for robust and accurate medical image segmentation
(LFB-Net)

We formulate the segmentation process as a recurrent framework using two deep learning networks interconnected via feedback loop

Feedback loop: use output error signal to make adjustments on the input single [1]

[1] Huh M., *et al.* (2019), CVPR.
Girum K.B., *et al.* (2020), IEEE Trans Med Imaging.

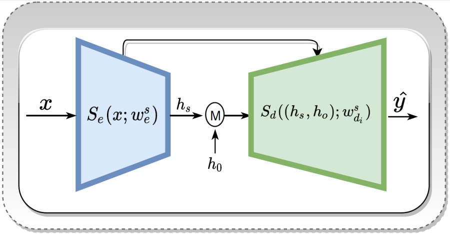
LFB-Net



Girum K.B., *et al.* (2020), IEEE Trans Med Imaging.

Forward system

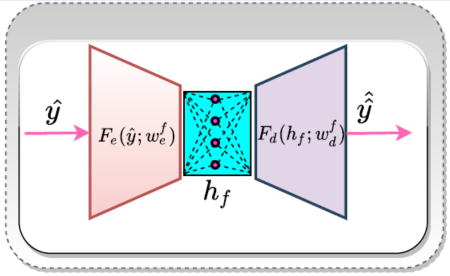
- Similar to U-net [1]
- Encoder: $S_e : x \mapsto h$
- Decoder: $S_d : h \mapsto y$
- $\hat{y} = S(x) = S_d(S_e(x))$
- $L(y, \hat{y})$
- x is the input image
- h the latent space
- $\hat{y}$ the predicted image



[1] Ronneberger O., *et al.* (2015), MICCAI.

Feedback system

- Similar to FCN [1]
- Encoder: $F_e : \hat{y} \mapsto h_f$
- Decoder: $F_d : h_f \mapsto \hat{\hat{y}}$
- $\hat{\hat{y}} = F(\hat{y}) = F_d(F_e(\hat{y}))$
- $L(y, \hat{\hat{y}})$

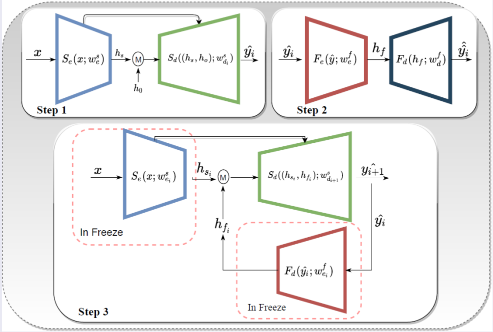


[1] Noh, H., *et al.* (2015), CVPR.

Integration: Segmentation with two systems

Recurrent process

- $\hat{y} = S(x) = S_d(S_e(x))$
- $\hat{\hat{y}} = F(\hat{y}) = F_d(F_e(\hat{y}))$
- $\hat{y}_{i+1} = S_{d_{i+1}}(h_{s_i}, F_{e_i}(\hat{y}_i))$



Experimental setup

Single label segmentation

1. Prostate
   - CT with seeds
   - 78 CT exams
2. Inner ear
   - 17 μCT exams [1]

Multi-label segmentation

1. Cardiac cine-MRI
   - ACDC MICCAI 2017 [2]
   - 150 exams
2. Echocardiography
   - CAMUS data [3]
   - 500 exams

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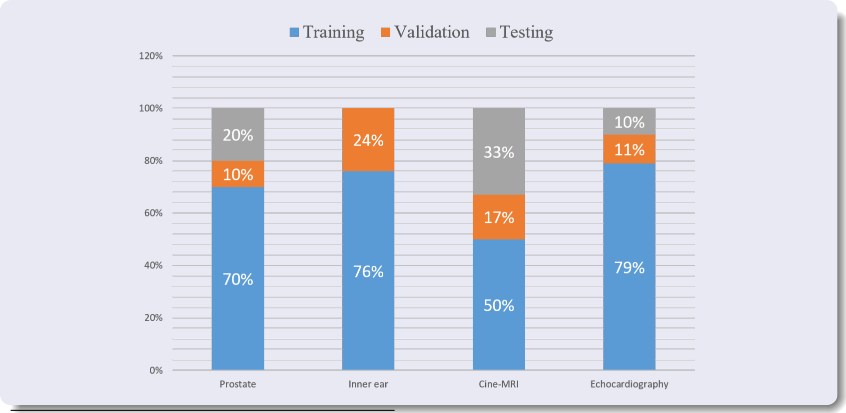
[1] Gerber N., *et al.* (2017), Sci. Data.

[2] Bernard O., *et al.* (2018), IEEE Trans Med Imaging.

[3] Leclerc S., *et al.* (2019), IEEE Trans Med Imaging.

Girum K.B., *et al.* (2020), IEEE Trans Med Imaging.

Experimental setup



[1] Gerber N., *et al.* (2017), Sci. Data.For the inner ear segmentation

[2] Bernard O., *et al.* (2018), IEEE Trans Med Imaging. For the cardiac cine-MRI segmentation

[3] Leclerc S., *et al.* (2019), IEEE Trans Med Imaging. For the echocardiographic image segmentation

Girum K.B., *et al.* (2020), IEEE Trans Med Imaging.

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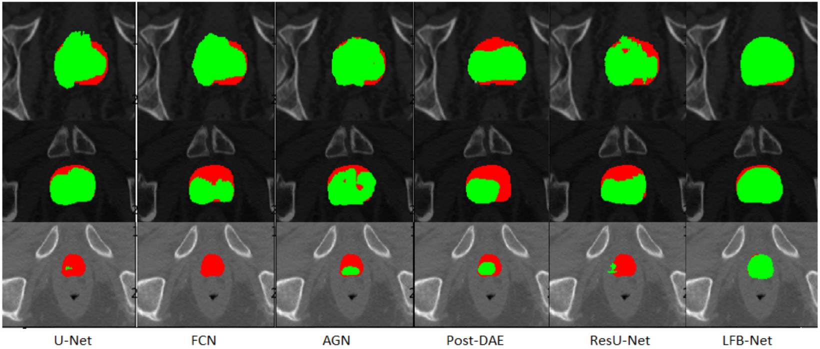
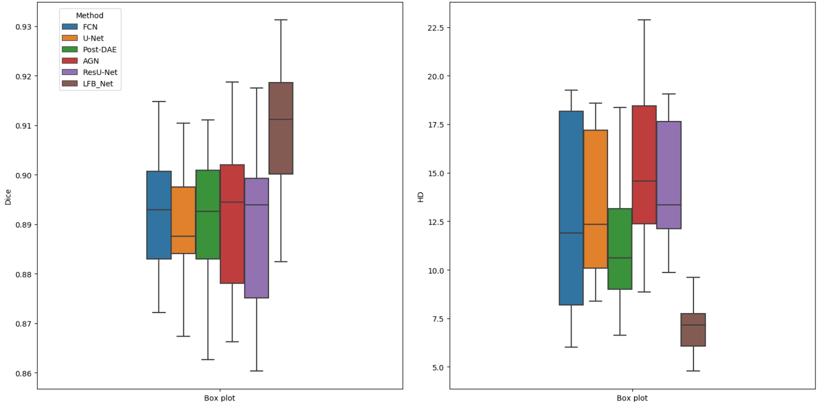
Prostate segmentation



[1] Noh H., *et al.* (2015), CVPR. [2] Ronneberger O., *et al.* (2015), MICCAI.
[3] He K., *et al.* (2016), CVPR. [4] Larrazabal A.J., *et al.* (2020), IEEE Trans Med Imaging.
[5] Schlempe J., *et al.* (2019), Med Image Anal.

Prostate segmentation

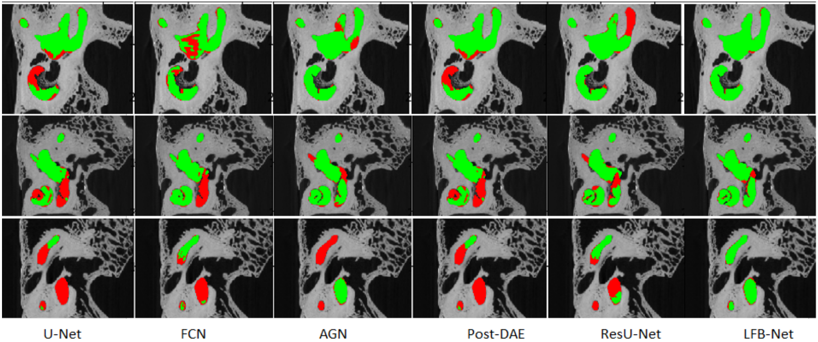


[1] Noh H., *et al.* (2015), CVPR. [2] Ronneberger O., *et al.* (2015), MICCAI.

[3] He K.*et al.* (2016), CVPR. [4] Larrazabal A.J. *et al.* (2020) IEEE Trans Med Imaging..

[5] Schlempe J. *et al.* 2019 Med Image Anal.

Inner ear segmentation



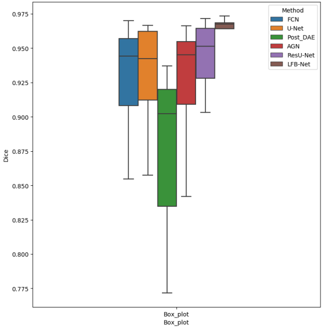
Ground truth in red, predicted in green

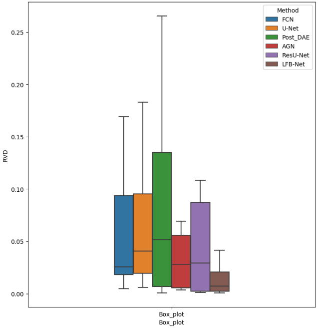
[1] Noh H., *et al.* (2015), CVPR. [2] Ronneberger O., *et al.* (2015), MICCAI.

[3] He K., *et al.* (2016), CVPR. [4] Larrazabal A.J., *et al.* (2020), IEEE Trans Med Imaging.

[5] Schlempe J., *et al.* (2019), Med Image Anal.

Inner ear segmentation



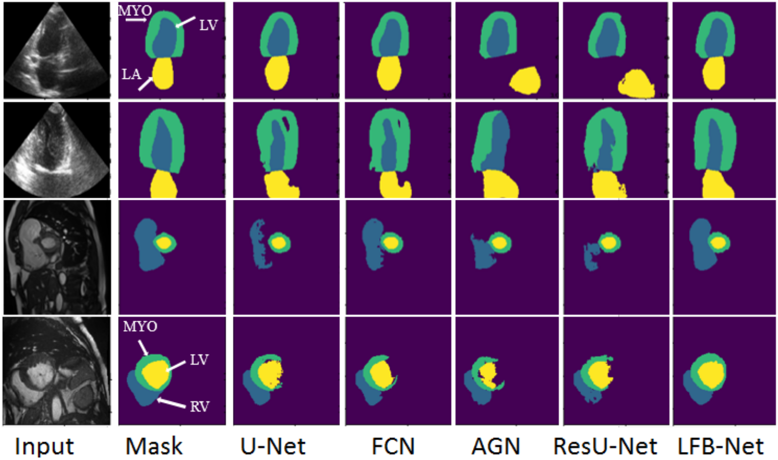


[1]Noh H., *et al.* (2015), CVPR. [2]Ronneberger O., *et al.* (2015), MICCAI.

[3] He K.*et al.* (2016), CVPR. [4]Larrazabal A.J. *et al.* (2020) IEEE Trans Med Imaging..

[5]Schlempe J. *et al.* 2019 Med Image Anal.

Multi-label segmentation



Echocardiographic image segmentation

	LV: Endocardium				LV: Epicardium				Left Atrium			
	Dice		HD		Dice		HD		Dice		HD	
Method	ES	ED	ES	ED	ES	ED	ES	ED	ES	ED	ES	ED
inter-observer	0.873	0.919	6.6	6.0	0.890	0.913	8.6	8.0	-	-	-	-
	±0.060	±0.033	±2.4	±2.0	±0.047	±0.037	±3.3	± 2.9	-	-	-	-
Intra-observer	0.930	0.945	4.5	4.6	0.951	0.957	5.0	5.0	-	-	-	-
	±0.031	±0.019	±1.8	±1.8	±0.021	±0.019	±2.1	±2.3	-	-	-	-
Oktay O. *et al.* [1]	0.913	0.936	5.6	5.6	0.945	0.953	5.9	5.9	0.911	0.881	5.8	6.0
Leclerc S. *et al.* [2]	0.912	0.936	5.5	5.3	0.946	0.956	5.7	**5.2**	0.918	0.889	5.3	5.7
U-net-2 [2]	0.899	0.922	5.3	5.7	0.923	0.932	6.4	6.4	0.888	0.848	6.2	6.9
LFB-Net	**0.926**	**0.946**	**4.8**	**4.8**	**0.952**	**0.959**	**5.2**	**5.2**	**0.924**	**0.902**	**5.0**	**5.2**

[1] Oktay O., *et al.*, *et al.* (2017), IEEE Trans Med Imaging.

[2] Leclerc S., *et al.* (2019), IEEE Trans Med Imaging.

Validation vs Testing

- Cardiac cine-MRI segmentation

Method	Dice		HD (mm)	
	Valid.	Test.	Valid.	Test.
AGN [1]	0.910±0.07*	0.894±0.09*	10.9±7.13	12.0±8.23*
FCN [2]	0.903±0.07*	0.890±0.08*	11.0±7.22	12.0±6.53*
U-Net [3]	0.906±0.06*	0.888±0.10*	11.5±7.50	12.3±7.79*
ResUnet [4]	0.903±0.07	0.893±0.09*	11.9±8.39*	11.9±7.32*
LFB-Net	**0.921±0.05**	**0.920±0.06**	**9.9±6.47**	**9.7±6.18**

[1] Schlempe J. *et al.* (2019) Med Image Anal.

[2] Noh H., *et al.* (2015), CVPR.

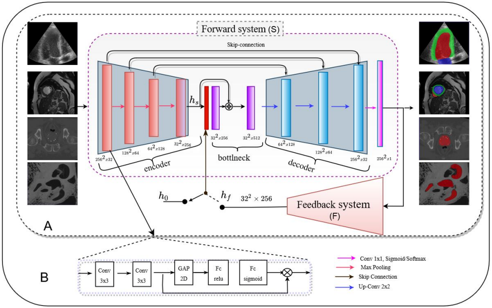
[3] Ronneberger O., *et al.* (2015), MICCAI.

[4] He K. *et al.* (2016), CVPR.

* corresponds to $p<0.05$.

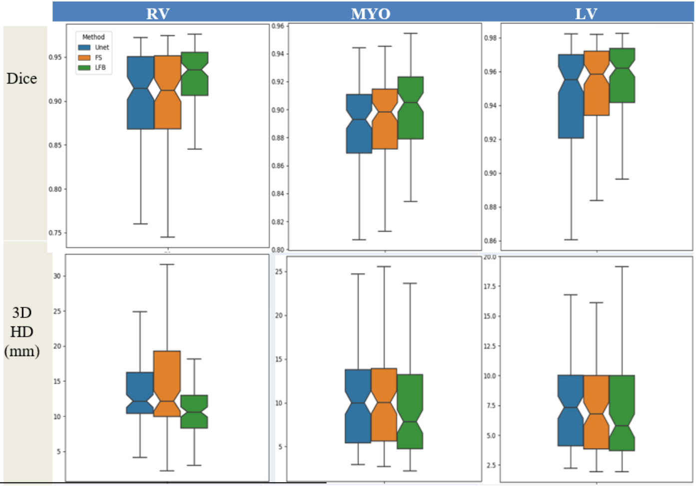
Ablation study

1. System design
2. Integration strategy
3. Training scheme



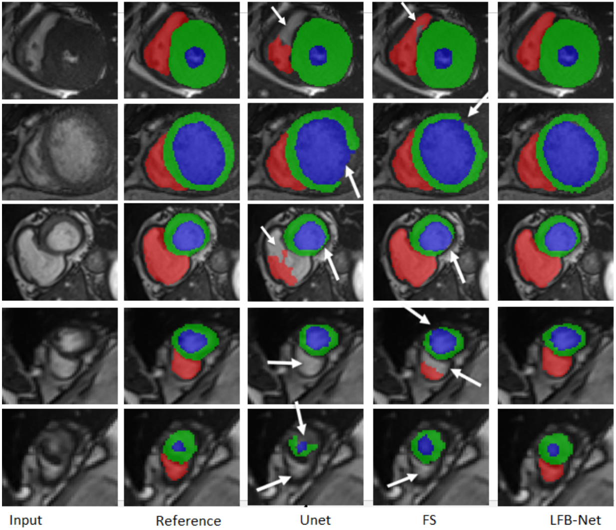
Girum K.B., *et al.* (2020), IEEE Trans Med Imaging.

Ablation study of system design: cardiac cine-MRI



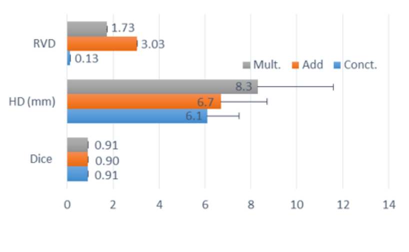
Unet: Forward system; FS: Forward system with squeeze-and-excitation network block; and LFB: Our method.

Ablation study of system design

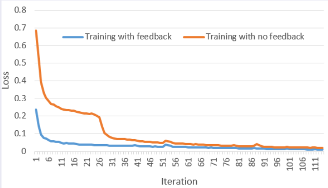


Ablation study of system integration and training strategy

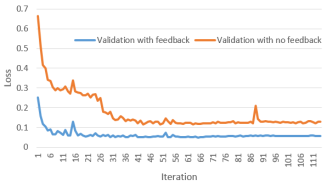
Integration strategy



Training loss



Validation loss



Conclusions

- Proposed and extensively evaluated a new fully automatic deep learning framework for medical image segmentation
- Experimental results revealed two important points:
    1. A feedback loop-based segmentation produces both plausible and accurate segmentation results
    2. It also produces results with reduced segmentation variability among the testing data, yielding state of the art results

Future perspectives

- Extend to other medical image analysis tasks
- Efficiently leverage the contextual feedback loop's latent space
- Efficiently leverage the merged contextual information
- 3D version of the proposed method could be applied in cases of available 3D datasets

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